

Spatiotemporal analysis of rainfall erosivity in Oklahoma

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ABSTRACT

The Universal Soil Loss Equation (USLE) and its family of models have been used for soil loss prediction and erosion mitigation. These empirical models relied on precipitation data predating 1957 to calculate the *Rainfall Erosivity (R-factor)* value; however, the isoelement map published in AH703 is still widely used in soil loss estimations today. Climatic and precipitation changes have presented questions about the validity and reliability of using these estimation methods. Additionally, instrumentation, precipitation gauging networks, and data availability have improved since the original publication of the AH703 isoelement map. This study conducted a spatiotemporal analysis in the GIS environment to estimate modern rainfall erosivity across Oklahoma using high-resolution rainfall data. Average annual and monthly rainfall erosivity factors, *R-factor* and *R_m-factor*, respectively, were estimated using 5-min interval rainfall data collected from 111 Oklahoma Mesonet sites. The sites had an average historical precipitation record of 28 years. Using new rainfall erosivity values, spatial variation was assessed within two geographical segments: a) NOAA-defined state climate divisions and b) EPA-defined Level III ecoregions. Temporal analysis revealed that rainfall erosivity occurring between April and October contributed 86% of the annual R-factor. This study also developed an updated isoelement map for the state of Oklahoma. The updated R-factor significantly differed from the original AH703 isoelement map. Specifically, comparing the isoelement maps revealed that the R-factor changed between −20% and 112%. The reasons contribute to the discrepancies between the two maps are also discussed.

1. Introduction

Water erosion refers to the detachment and transportation of soil particles from their original location due to the action of water (Ellison, 1950). Water erosion poses significant economic, social, and environmental risks, such as degradation of water quality (Nugues and Roberts, 2003; Issaka and Ashraf, 2017), reduction of agricultural productivity and dampening agricultural economy (Boardman et al., 2003; Meena et al., 2017; Sartori et al., 2019; Thaler et al., 2021). Furthermore, the degraded land due to water erosion cannot support the same vegetation density (Alemu, 2014), minimizing the greenhouse gas absorption (Rice and Reed, 2007; He et al., 2024).

The significant impacts of erosion have been widely recognized. The Universal Soil Loss Equation (USLE) was developed by the U.S. Department of Agriculture (USDA) to measure water erosion (Smith and Wischmeier, 1962). This equation comprises six input factors including

rainfall erosivity, soil erodibility, slope steepness, slope length, cover-management and supporting practice.

Rainfall erosivity, as one of input factors in the Universal Soil Loss Equation, reflects the combined effects of rainfall drops and runoff on soil erosion over a long-term period.

The rainfall erosivity of a single storm (EI_{30}) is defined as the product of the total kinetic energy of the storm (E) and its maximum 30-min rainfall intensity (I_{30}) (Wischmeier, 1959). To capture those characteristics within a single rainfall event, high temporal resolution rainfall data with long-term historical recordings is required. The sum of storm EI_{30} for a given period is a numerical measure of the erosivity potential of the rainfall within that period. The storm EI_{30} enables the derivation of seasonal values, which are vital for accurately predicting soil loss. Moreover, these estimates play a crucial role in assessing cover-management which exhibit seasonal variability (Wischmeier and Smith, 1978; Renard, 1997; USDA-ARS, 2013).

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Several maps of rainfall erosivity have been developed and integrated into software such as the USLE, Revised Universal Soil Loss Equation (RUSLE), serving as a database to provide localized rainfall erosivity values for soil loss assessment under specific site conditions. The isoerodent maps for eastern United States were originally produced using rainfall data from 1936 to 1957, presented as contour lines indicating average annual rainfall erosivity (*R-factor*) in USLE (Smith and Wischmeier, 1962). Due to the lack of long-term high temporal resolution data, the western United States was excluded from the original map. The isoerodent map was later extended to Pacific Coast and Hawaii using 15-min interval rainfall data, which were incorporated into the RUSLE (Renard, 1997).

Rainfall erosivity values are inherently tied to changes in rainfall patterns, which are not temporally stationary (Huff and Angel, 1992; Hollinger et al., 2002). Given the increasing impact of climate change on rainfall patterns and its influence on rainfall erosivity and spatial variability, there is a growing need to enhance robust methods for rainfall erosivity estimation and to update erosivity databases (Dabney et al., 2012). However, the development of such datasets faces significant challenges. In addition to lacking high temporal resolution rainfall data, current interpolation methods do not sufficiently capture spatial complexities. Specifically, the *R-factor* values between isoerodent lines are typically derived through linear interpolation, resulting in maps that lack sufficient precision to represent variations in *R-factor* across complex terrains, such as mountainous and valley regions.

The concept of erosivity density was introduced to quantify the erosive potential per unit of precipitation, and its values vary spatially in a less tortuous manner (USDA-ARS, 2013). Thus, monthly erosivity density was interpolated using kriging method and subsequently employed to estimate monthly rainfall erosivity in RUSLE2 (USDA-ARS, 2013). Erosivity density for each month was derived from 15-min gauge precipitation data (DSI-3260) archived by the National Oceanic and Atmospheric Administration's National Centers for Environmental Information, covering the period from the 1960s to the 1990s. Monthly rainfall erosivity was then estimated by multiplying the erosivity density by the average monthly precipitation obtained from the Precipitation-Elevation Regressions on Independent Slopes Model (PRISM) database. The integration of gridded PRISM data effectively mitigates the challenges posed by missing 15-min precipitation gauge records in the erosivity density database. The gridded PRISM precipitation dataset ensures smoother spatial transitions of rainfall erosivity and enhances the accuracy of soil loss assessments.

The DSI-3260 15-min precipitation data was used to later update annual rainfall erosivity map for the conterminous United States using data from 1970 to 2013 (McGehee et al., 2022). However, this study does not represent a definitive analysis of rainfall erosivity across the U. S. The quality of the 15-min precipitation data is compromised by missing and accumulated values, necessitating the application of gap-filling technique (McGehee and Srivastava, 2018). Although gap-filling is critical for complete analysis, it affects the accuracy of rainfall erosivity. Furthermore, rainfall erosivity values derived from 15-min resolution precipitation data tend to be lower than those estimated from finer-resolution data due to the dampening effect of coarser temporal resolution on rainfall intensity (Flanagan et al., 2020). Additionally, irregular spatial trends emerge in the updated map after the interpolation into raster format.

There have also been efforts to develop global rainfall erosivity. A global gridded monthly rainfall erosivity database was developed through extensive data collection from approximately 4000 sites across 65 countries, using an ensemble machine learning approach (Panagos et al., 2023). This interpolation method enables the global rainfall erosivity maps to exhibit smooth and continuous spatial variation, meeting the requirements of modeling applications (Dingman, 2015). However, the database faces limitations due to the use of datasets with varying temporal resolutions and recording lengths, which can impact the accuracy of the maps, as rainfall erosivity is not temporally

stationary. Moreover, the algorithm employed for global rainfall erosivity estimation may not perform optimally in regions with high rainfall erosivity. Therefore, regional studies are essential to apply equations that are best suited to local conditions for more accurate computation of rainfall erosivity.

The state of Oklahoma, located in the Southern Great Plains region of the United States, features a diverse climate. According to the Köppen climate classification, Oklahoma's climate ranges from humid subtropical in the east to semi-arid in the west, with precipitation patterns varying by season (Oklahoma Climatological Survey, 2024). Oklahoma also offers the nation's most diverse terrain, encompassing ecoregions that span from mesas to mountains (Gourley and Park, 2012). The spatial and temporal variation in rainfall erosivity across Oklahoma is essential for development of regional soil conservation practices.

The primary objective of this study is to estimate monthly rainfall erosivity using high temporal resolution (5-min interval) rainfall data with denser spatial distribution over the state of Oklahoma, which serves as regional data pools of rainfall erosivity. In addition, the spatial analysis is conducted within recognized divisions based on two approaches: (1) climate divisions defined by the National Oceanic and Atmospheric Administration (NOAA), and (2) eco-regions defined by the Environmental Protection Agency (EPA). The spatial trends of modern rainfall erosivity were compared with these divisions, in an effort to facilitate the adoption of updated rainfall erosivity factors for soil loss estimates and conservation efforts. Furthermore, the annual rainfall erosivity map using modern records was also generated to evaluate the difference from the isoerodent map in Agricultural Handbook No. 703 (AH 703).

2. Materials and methods

2.1. Study area

The state of Oklahoma is in the south-central United States, and spans latitudes 33°37' N to 37° N and longitudes 94°26' W to 103° W, covering an area of 181,030 km². The normal annual precipitation (averaged over 30 years) between 1991 and 2020 ranged from 409 mm in the western panhandle to 1752 mm in the southeast, as reported by PRISM Climate Group (<https://prism.oregonstate.edu/>). Fig. 1 shows the geographical boundaries of the state, along with the annual average precipitation color contours, established using data the PRISM data (data range: 1991–2020). Oklahoma experiences high frequency and intensity of extreme storm events (Rahmani et al., 2016; Kloesel et al., 2018). These storms can lead to increased erosion (Edwards and Owens, 1991; Larson et al., 1997; Wang et al., 2016), particularly in the Northeast (Harmel et al., 1999), southwestern (Gilley et al., 1997; Moriasi et al., 2020), and central regions (Garbrecht and Zhang, 2015). It is estimated that 50 million tons of soil are eroded each year from agricultural land in Oklahoma (Warren, 2010).

For this study, spatial analysis within two divisions was conducted: (1) climate divisions designed by NOAA; and (2) ecoregions defined by EPA. Climate divisions are demarcated based on historical data concerning drought, temperature precipitation, and heating and cooling degrees (Karl and Koss, 1984) for agricultural and hydrological applications (Guttman and Quayle, 1996). Oklahoma is divided into nine climate divisions. The geographic boundaries defining these climate divisions were obtained in the form of a GIS shape file from the National Integrated Drought Information System (NIDIS, n.d.).

On the other hand, the EPA separates the country into ecoregions. The purpose evolved into facilitating ecosystem management considering the patterns and composition of biotic and abiotic phenomena including geology, landforms, soils, vegetation, climate, land use, wildlife, and hydrology (Omernik and Griffith, 2014). A hierarchical scheme with Roman numerals has been adopted for different levels of ecological regions ranging from general to more detailed with the number increases. Level I and Level II ecological regions are delineated

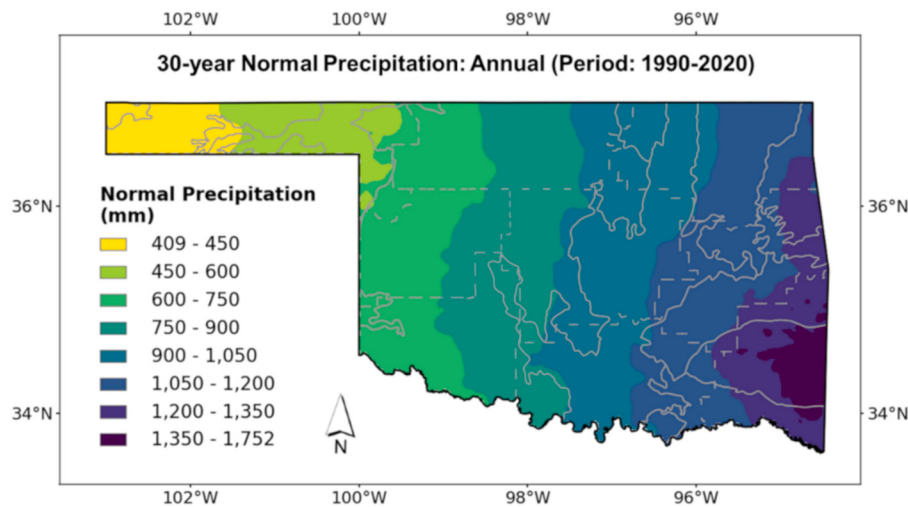


Fig. 1. Color Contours Showing Normal Precipitation Values for Oklahoma, Based on Data Obtained from the PRISM Climate Group (Data Range: 1991–2020). Normal Precipitation Refers to the Average Annual Precipitation Value Taken Over a 30-year Period.

for global and national scales respectively. Level III is for regional areas within Level II regions (Omerik and Griffith, 2014). In Oklahoma, there are 12 Level III ecoregions, which were used for this analysis.

Both climate divisions and ecoregions were used in this study to characterize the spatial distribution of rainfall erosivity. Fig. 2 presents maps of Oklahoma along with the boundaries for the climate divisions (Fig. 2a), and the ecoregions (Fig. 2b). The maps also show locations of the Mesonet sites within each homogeneous segment. Table 1 lists the characteristics of the divisions used in this study.

2.2. Rainfall data and preprocessing

The Oklahoma Mesonet was commissioned in 1994 as a world-class network of environmental monitoring stations (Brock et al., 1995). There are 120 total Mesonet sites covering the entire state, with at least one Mesonet site in each of the 77 counties. Fig. 2a and b, show the distribution of the Mesonet sites within each climate division and ecoregion, respectively. Among climate divisions, the distribution of Mesonet sites is relatively balanced, with the number of sites ranging between 8 (in the Panhandle and West Central divisions) to 20 (in the Central division) (refer to Table 1a). On the other hand, the distribution of Mesonet sites in ecoregions is uneven. The Central Great Plains ecoregion has the greatest number (47) of sites; the East Central Texas Plains ecoregion has only one Mesonet site, whereas the Boston Mountains ecoregion has none (see details in Table 1b).

At each Mesonet site, the accumulated precipitation (including rainfall and frozen precipitations) is measured above the ground using a tipping-bucket rain gauge. The rain gauge tips with every 0.254 mm (0.01 in.) of measurable rainfall. A running accumulation of rainfall is measured every 5 min starting at 0000 UCT (6 PM CST) before being reset to zero at 00:00 AM CST. When the rainfall is very light, it may be recorded at 15-min intervals, even if the rain is continuous. The rainfall data used in this study was collected at 5-min intervals between 1994 and Esri, 2024. The data was obtained in .CSV format, with the total file size exceeding 20 GB. All computations for this study were carried out using the Python programming language using the Pandas package (McKinney, 2010).

Upon preliminary analysis, it was observed that not all Mesonet sites recorded data spanning the entire period of interest. For the current analysis, we eliminated all sites with data in less than 10 years. This resulted in the elimination of 9 sites. This resulted in data analysis from 111 total OK Mesonet sites, with data ranging between 10.6 years and 30.1 years. Out of these, 96 sites had data for at least 26 years. Fig. 3

shows the frequency distribution of the Mesonet sites that recorded data over different durations. This rainfall data was selected for this study due to its long duration and high resolution of available data.

2.3. Rainfall erosivity calculations

Rainfall erosivity were calculated in this study with the method described by USDA-ARS (2013).

Storms with less than 12.5 mm of rainfall were excluded from the storm erosivity computations (USDA-ARS, 2013). The (I_{30}) value was taken to be the maximum 30-min intensity observed during a storm (USDA-ARS, 2013), and was calculated by using a rolling window method, where a 30-min window moves through the rainfall data at 5-min intervals. The maximum of rainfall amount within 30 min for a storm was identified and was used to calculate I_{30} . For storms lasting less than 30 min, the magnitude of I_{30} was taken to be twice the amount of total precipitation (USDA-ARS, 2013). A detailed example illustrating the computation approach for EI_{30} has been provided in the supplementary data section of this manuscript. The rainfall erosivity values calculated from individual storms were aggregated to calculate long-term average annual and monthly erosivity factors (R -factor and R_m -factor, respectively). Fig. 4 presents a flow chart depicting the overall workflow used in this study. A sample calculation is included in the supplementary material.

2.4. Assessing the spatial variation in rainfall erosivity

Climate divisions and Level III ecoregions were used to analyze spatial variation in rainfall erosivity within the state of Oklahoma. The annual or monthly average erosivity factors (R -factor or R_m -factor, respectively) were averaged across all Mesonet sites within a given homogeneous sub-division (climate division and ecoregion) to calculate the mean R -factor or mean R_m -factor values per homogeneous area of consideration.

2.5. Production of raster maps for rainfall erosivity

Raster maps for the annual and monthly rainfall erosivity factors were developed using ArcGIS Pro (Esri, 2024). Ordinary kriging, employing an exponential semivariogram model (Oliver and Webster, 1990), was chosen to interpolate the raster maps from point data representing the Mesonet sites. This approach was deemed the most suitable for 30-m spatial interpolation of rainfall across a basin (Earls and

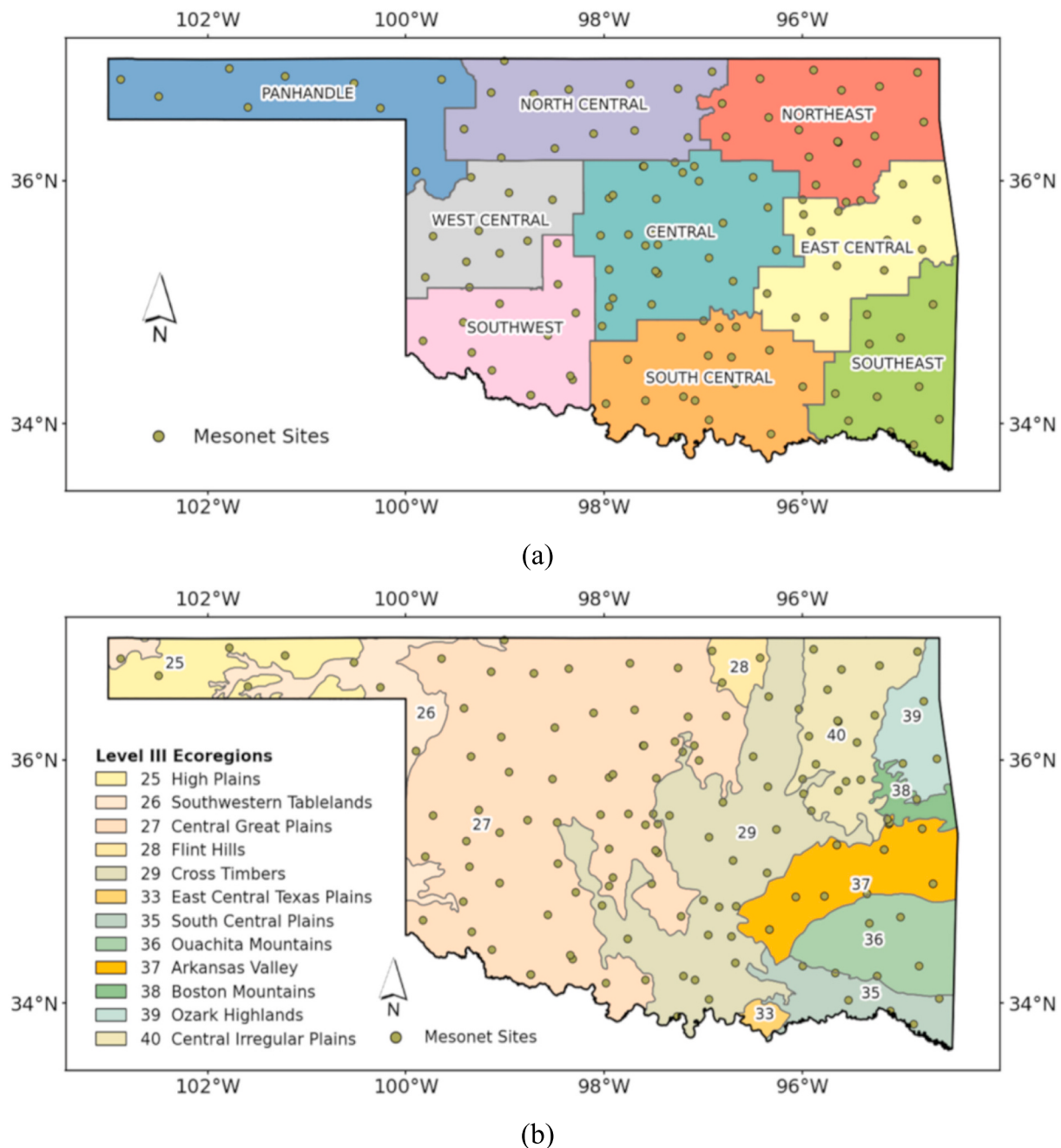


Fig. 2. Spatial Distribution of the Mesonet Sites in Oklahoma with Boundary Demarcations Corresponding to: (a) Climate Divisions; (b) Eco-Regions.

Dixon, 2007) and was found to be independent of the influence of spatial resolution on interpolation results (McGehee et al., 2022). The *R-factor* on the isoerodent map reported in Agriculture Handbook No. 703 (AH703) (Renard, 1997) was also digitized to create a raster map using the Topo to Raster tool (Hutchinson, 1988). The isoerodent contour lines served as input parameters, while all other interpolation settings remained at their default values. The isoerodent map, thus digitized, has been referred to as the “published map” in this manuscript, and has been used as the baseline when discussing the newly developed maps. To quantify the difference between the new and published maps, the relative change (%) in erosivity factor was calculated using the Raster Calculator tool (Esri, 2024). All raster maps were generated in the NAD 1983 Albers projection with a 30-m spatial resolution. The geo-processing was conducted with ArcPy (Esri, 2024), which is a Python site package provided by ArcGIS Pro; the mapping was processed by

GeoPandas (Jordahl, 2014).

3. Results and discussions

3.1. Seasonal variability in rainfall erosivity factor

The first objective of this effort was to assess the temporal variability in the rainfall erosivity factors calculated from the 111 Mesonet sites across Oklahoma. Five-minute interval rainfall data was used along with the kinetic energy equations to calculate the monthly as well as the annual average erosivity factor values (*R_m-factor* and *R-factor*, respectively). The results have been listed in Table 2.

From Table 2, the average annual erosivity factor (*R-factor*) for the Mesonet sites ranged between 1227 and 9988 MJ mm ha⁻¹ h⁻¹ yr⁻¹ with a mean value (across all Mesonet sites) of 5605 MJ mm ha⁻¹ h⁻¹

Table 1

Characteristics of Area Divisions Used in this Study (a) Climate Divisions; and (b) Ecoregions.

(a)			
Climate divisions	Area (km ²)	Area Proportion (%)	No. of Mesonet Sites
Central	26,463	14.6	20
East Central	18,489	10.2	12
North Central	21,048	11.6	12
Northeast	22,058	12.2	15
Panhandle	20,669	11.4	8
South Central	22,108	12.2	16
Southeast	16,738	9.2	9
Southwest	17,905	9.9	11
West Central	15,563	8.6	8

(b)			
Ecoregions	Area (km ²)	Area Proportion (%)	No. of Mesonet Sites
Arkansas Valley	12,453	6.9	8
Boston Mountains	2147	1.2	0
Central Great Plains	73,251	40.5	47
Central Irregular Plains	13,486	7.4	12
Cross Timbers	34,359	19.0	21
East Central Texas Plains	980	0.5	1
Flint Hills	2498	1.4	3
High Plains	9115	5.0	3
Ouachita Mountains	10,479	5.8	4
Ozark Highlands	6118	3.4	4
South Central Plains	6853	3.8	4
Southwestern Tablelands	9299	5.1	4

yr⁻¹. Mean R_m -factor values ranged from 107 to 975 MJ mm ha⁻¹ h⁻¹ yr⁻¹. The highest mean R_m -factor was observed for the month of May, accounting for 17.4% of the mean (across all Mesonet sites) R -factor. On the other hand, the lowest mean R_m -factor was observed for the month of February, accounting for only 1.9% of the mean R -factor value. These trends have been represented in Fig. 5 in the form of column plots. As seen from the Fig. 5, the mean R_m -factor remains low and consistent during the months of January and February. However, from March to May, there is a significant increase. From April to October, the mean R_m -factor exceeds 500 MJ mm ha⁻¹ h⁻¹ yr⁻¹, contributing 85% to the

mean R -factor. In contrast, the months of January, February, November, and December each have mean R_m -factor values below 300 MJ mm ha⁻¹ h⁻¹ yr⁻¹. From these values, it is apparent that mean (across all Mesonet sites) R_m -factor values show significant variations from one month to another. This highlights the importance of targeted and dynamic soil conservation practices to ensure they can accommodate the months with the highest erosivity factor values. Ideally, soil conservation practices should be planned according to the monthly variations in rainfall erosivity to protect soil health and agricultural productivity.

Average monthly erosivity factor (R_m -factor) maps were generated for the state of Oklahoma; 12 maps were generated for the 12 months (see Fig. 6). In these maps, R_m -factor values exceeding 500 MJ mm ha⁻¹ h⁻¹ yr⁻¹ occur in the months with heavy rains (Howard, 2010): April, May, June, July, August, September, and October. In those months, more than 50% of the state's geographic area have R_m -factors >500 MJ mm ha⁻¹ h⁻¹ yr⁻¹, with nearly 90% of the state exceeding this value in May. Monthly changes in rainfall erosivity were found to be significant across Oklahoma, as demonstrated in Fig. 6. The variability in rainfall erosivity throughout the year emphasizes the need to consider season-appropriate crop management strategies to reduce soil loss when rainfall erosivity is high (Wischmeier and Smith, 1978; Renard, 1997). Additionally, soil loss predictions should be based on monthly erosivity data rather than relying solely on annual averages, as the latter may overlook periods of heightened soil erosion risk. Fig. 6, which illustrates the spatial distribution of monthly rainfall erosivity, can provide information to select and implement appropriate erosion-control practices to mitigate soil loss, such as establishing season-appropriate cropping and vegetation. Monthly estimates of rainfall erosivity are important for soil loss estimates and mitigation, specifically when considering appropriate cover management and support practices. Moreover, the value of mean R_m -factor also can be used to estimate the seasonal cover-management factor (C -factor).

3.2. Spatial variability in rainfall erosivity factor

The spatial trend of rainfall erosivity was analyzed based on two approaches to sub-divide the state of Oklahoma into regions: (1) NOAA-defined climate divisions, and (2) EPA-defined ecoregions. The mean R -factor values for each division (across all Mesonet sites per area division) were reported in Fig. 7.

Oliveira et al. (2013) used a threshold value of 5000 MJ mm ha⁻¹ h⁻¹ yr⁻¹ to identify locations in Brazil that were susceptible to medium to strong rainfall erosivity. The same threshold value was adopted in this

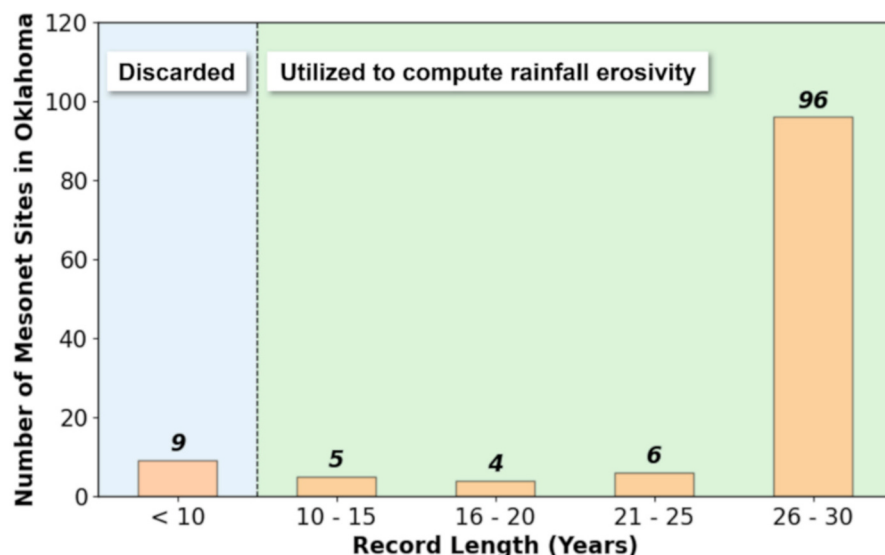


Fig. 3. Frequency Distribution of Mesonet Sites Providing Data Over Different Durations.

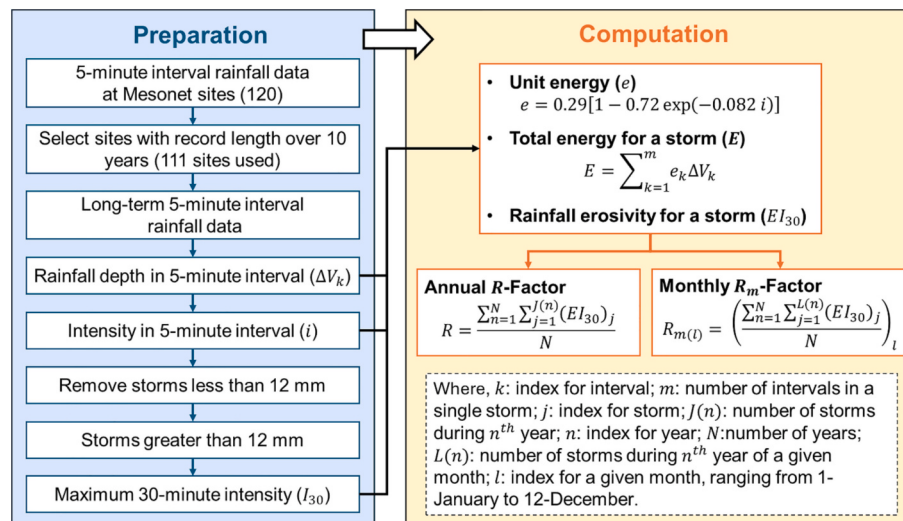


Fig. 4. Workflow for Rainfall Erosivity Computation using Mesonet Data and the Rainfall Kinetic Energy Equation.

Table 2

Mean (Across Mesonet Sites) Monthly and Annual Erosivity Factors Calculated for the State of Oklahoma.

Periods	Mean	Std	Min	Max	CoV
	$MJ \text{ mm ha}^{-1} \text{ h}^{-1} \text{ yr}^{-1}$				
Jan	116	103	0	469	0.89
Feb	107	73	0	386	0.69
Mar	269	135	17	647	0.50
Apr	518	222	74	1105	0.43
May	975	395	138	2103	0.40
Jun	853	289	119	1880	0.34
Jul	642	230	208	1477	0.36
Aug	634	230	224	1345	0.36
Sep	572	270	80	1472	0.47
Oct	550	214	78	1053	0.39
Nov	215	168	2	752	0.78
Dec	153	132	0	763	0.86
Annual	5605	1722	1227	9988	0.31

study. From Fig. 7a, five out of the nine climate divisions (Southeast, East Central, Northeast, South Central, and Central divisions) had mean R -factor values exceeding $5000 \text{ MJ mm ha}^{-1} \text{ h}^{-1} \text{ yr}^{-1}$. These climate

divisions contribute 57.8% of the state's total area. The mean (across all Mesonet sites) R_m -factor values per climate division have been listed in Table 3a. The Central, East Central, Northeast, and Southeast climate divisions demonstrate the highest mean R_m -factor. The Central division shows the highest mean R_m -factor in June and August; East Central has the highest mean R_m -factor in April, May, July, and October. The panhandle division consistently has the lowest R_m -factor for all months.

When analyzed by ecoregion, the mean R -factor in eight of the twelve ecoregions was above $5000 \text{ MJ mm ha}^{-1} \text{ h}^{-1} \text{ yr}^{-1}$ (see Fig. 7b). The Ouachita Mountains ecoregion had the highest mean R -factor value of $8317 \text{ MJ mm ha}^{-1} \text{ h}^{-1} \text{ yr}^{-1}$. The High Plains and Southwestern Tablelands were notable outliers with the lowest mean R factor values, registering at just 1547 and 2141 $\text{MJ mm ha}^{-1} \text{ h}^{-1} \text{ yr}^{-1}$, respectively. Referring to Table 3b, the Ouachita Mountains exhibited the highest mean R_m -factor in January, February, March, September, November, and December. The South-Central Plains had the highest mean value of R_m -factor in May. The priority for soil conservation efforts should be focused on the sub-regions with higher rainfall erosivity, as these areas might be more susceptible to soil loss and degradation.

One notable observation is that the mean values of the annual (R -factor) and the mean values of monthly rainfall erosivity (R_m -factor) differ when analyzed by ecoregions versus climate divisions (see

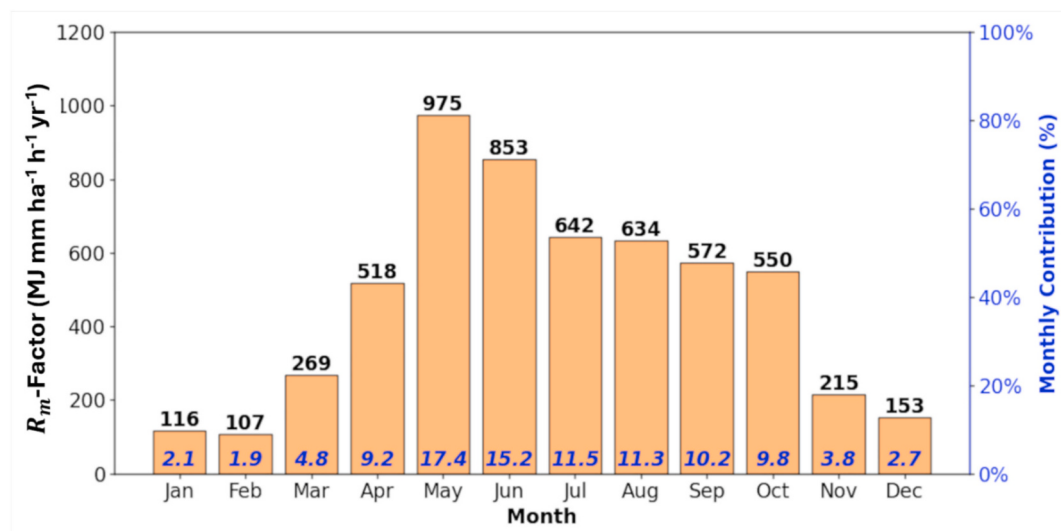


Fig. 5. Mean (Across all Mesonet Sites) R_m -factor Values and their Contributions mean (across all Mesonet Sites) R -factor (labels in % inside the base of columns).

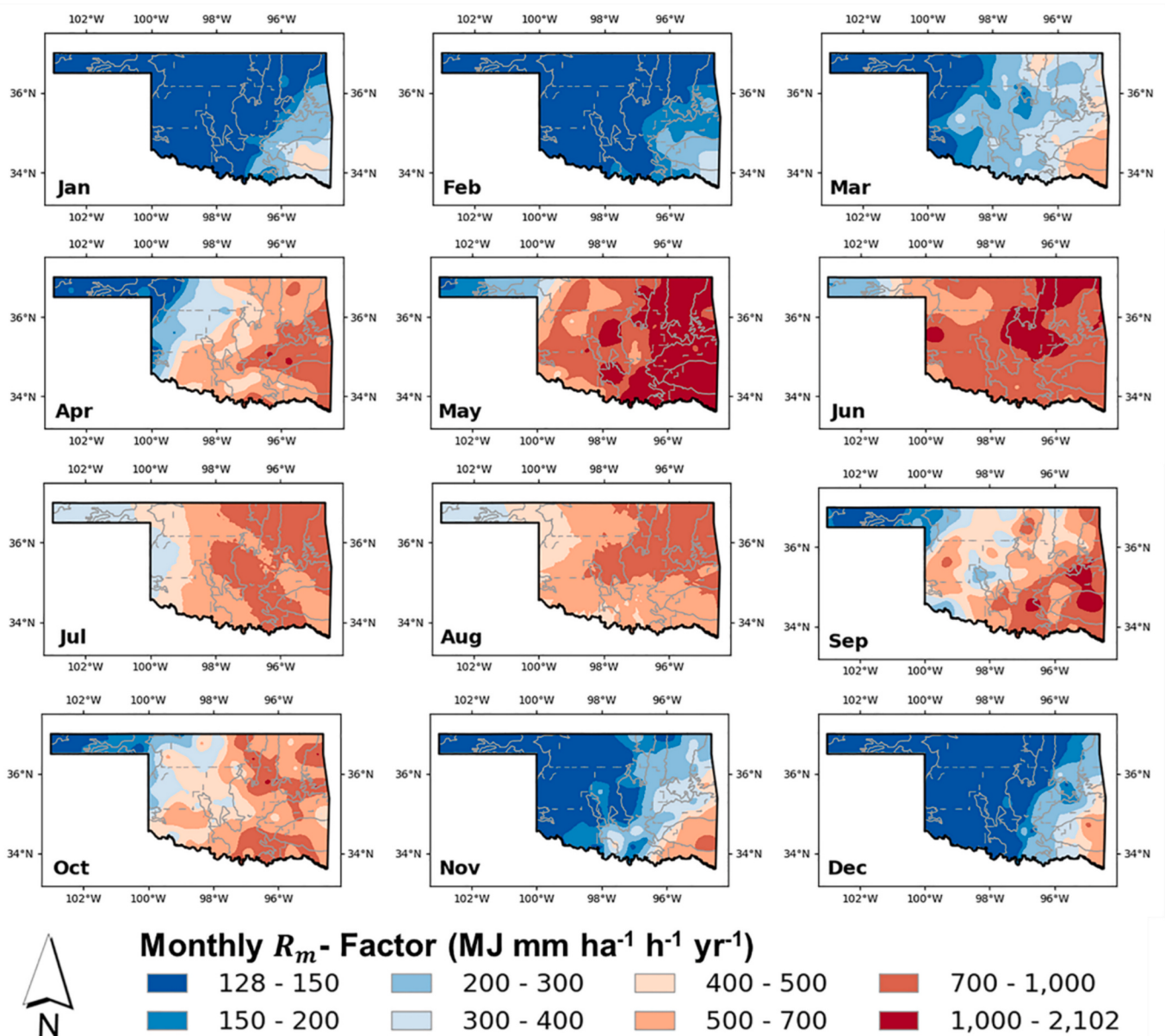


Fig. 6. Spatial Distribution of R_m -factor in Oklahoma.

Table 3). Additionally, the standard deviation of mean R -factor within climate divisions ranges from 481 to 984 $\text{MJ mm ha}^{-1} \text{h}^{-1} \text{yr}^{-1}$ (Fig. 7a), whereas across ecoregions, it exhibits a broader range, from 0 to 1558 $\text{MJ mm ha}^{-1} \text{h}^{-1} \text{yr}^{-1}$ (Fig. 7b). This difference in spatial patterns can be attributed to the variations in geographic segmentation frameworks. The total geographic area of the state is more evenly distributed among climate divisions than among ecoregions (see Table 1). Climate divisions each cover between 8.6% to 14.6% of the state's area; whereas ecoregions range from 0.5% to 40.5%. Also, climate divisions are defined based on temperature and precipitation (Karl and Koss, 1984), whereas ecoregions are delineated using a more comprehensive set of factors, including geology, landforms, soils, vegetation, climate, land use, wildlife, and hydrology (Omernik, 1987, 1995). A particularly notable case is the Ozark Highlands ecoregion, which covers only 3.4% of the state's total area yet exhibits the mean R -factor reaching 1558 $\text{MJ mm ha}^{-1} \text{h}^{-1} \text{yr}^{-1}$, the maximum among all ecoregions.

Based on the standard deviation of the mean R -factor and the spatial distribution of Mesonet sites within sub-regions, climate divisions appear to have a higher potential for classifying rainfall erosivity.

Ecoregions incorporate additional environmental factors such as geology, landforms, vegetation, and hydrology, which may better capture localized erosivity patterns. Thus, the considering these divisions in place of rainfall erosivity zones will require comprehensive analysis and in-depth discussion in future studies to facilitate localized implementations of soil conservation practices."

3.3. Updated R -factor map for Oklahoma

As the last task in the current study, a new R -factor map for Oklahoma was developed. This was done by interpolating from points of Mesonet sites that were used to calculate the R -factor values. For the sake of comparison, the original isoelement map published in AH703 was also digitized and rasterized. The two maps have been presented in Fig. 8. As seen from the figure, the R -factor values on both maps increase from north to south. However, the R -factor magnitudes on the updated map are considerably larger compared to those from the original isoelement map. For example, for the updated map (Fig. 8a) the R -factor ranges from 1227 to 9986 $\text{MJ mm ha}^{-1} \text{h}^{-1} \text{yr}^{-1}$, whereas on the original

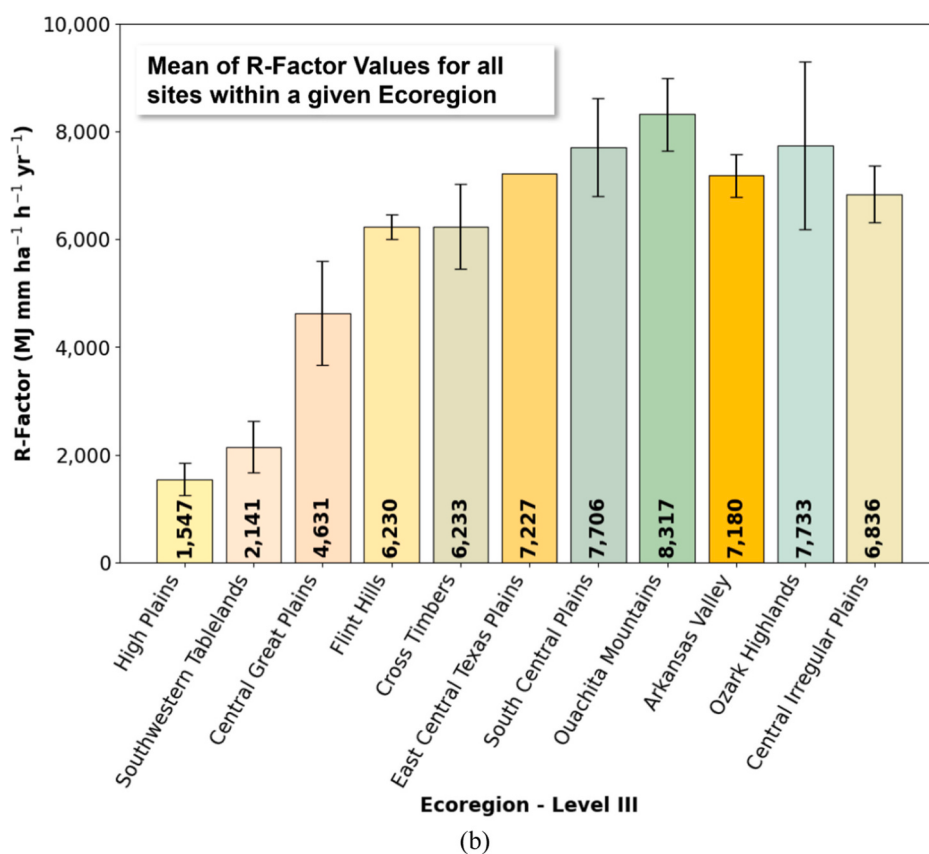
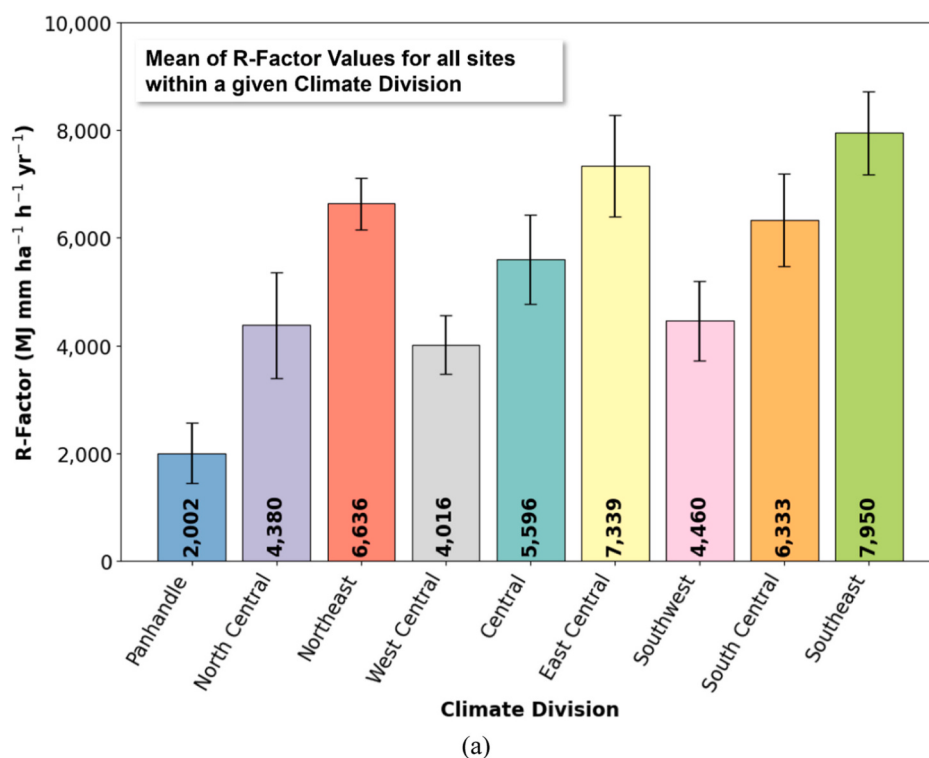


Fig. 7. Mean R-Factor Values Calculated Per (a) Climate Division; and (b) Ecoregion. Error Bars Represent the Standard Deviation of the Data.

Table 3Mean R_m -factor ($\text{MJ mm ha}^{-1} \text{ h}^{-1} \text{ yr}^{-1}$) Values Calculated Per (a) Climate Division; and (b) Ecoregion.

(a)													
Climate divisions	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec	Annual
Central	69	87	233	486	959	1037	712	767	454	520	157	114	5596
East Central	217	185	344	830	1273	903	779	729	785	691	342	261	7339
North Central	48	62	197	339	707	743	630	614	414	462	98	65	4380
Northeast	112	101	338	611	1273	1004	765	761	595	675	237	162	6636
Panhandle	17	10	48	120	255	411	384	393	148	164	19	33	2002
South Central	153	139	298	599	1184	832	662	529	816	686	267	168	6333
Southeast	358	258	550	728	1265	792	690	667	903	652	618	469	7950
Southwest	45	52	177	469	742	793	527	554	407	505	115	73	4460
West Central	45	47	192	284	699	839	375	479	538	375	88	55	4016

(b)													
Ecoregions	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec	Annual
Arkansas Valley	263	194	368	786	1136	906	661	733	851	611	358	315	7180
Boston Mountains	–	–	–	–	–	–	–	–	–	–	–	–	4631
Central Great Plains	52	65	196	403	776	846	583	606	446	462	117	78	6836
Central Irregular Plains	124	115	298	651	1477	930	736	788	579	674	271	192	6233
Cross Timbers	118	118	285	594	1101	966	686	636	709	658	219	144	7227
East Central Texas Plains	148	178	341	684	1213	804	908	466	884	854	502	246	6230
Flint Hills	90	97	430	624	985	896	844	726	618	652	184	86	1547
High Plains	3	1	40	112	194	228	348	331	106	150	7	25	8317
Ouachita Mountains	413	288	606	765	1272	897	655	559	1039	668	654	500	7733
Ozark Highlands	232	174	422	780	1227	1042	902	708	771	797	386	292	7706
South Central Plains	324	246	508	598	1479	637	785	696	733	711	585	404	2141
Southwestern Tablelands	22	17	50	122	273	444	381	445	174	155	25	34	7180

AH703 map, it ranged from 1079 to 5475 $\text{MJ mm ha}^{-1} \text{ h}^{-1} \text{ yr}^{-1}$ (Fig. 8b). To identify which areas of the state are more affected by these changes, Fig. 9 shows a color contour map showing the percent difference R -factor estimations across the state of Oklahoma by comparing the two map versions shown Fig. 8. From Fig. 9, the R -factor values have increased for most parts of Oklahoma, compared to what the values were according to the original AH703 isoerodent map. The maximum increase (112%) was observed for the Boston Mountains ecoregion.

One of reasons for discrepancies between the AH703 and the updated map lies in the rainfall data sources used. The AH703 isoerodent map was based on rainfall data from 1936 to 1957 whereas annual precipitation totals for 2002–2021 show notable differences compared to those from the first half of the 20th century (1901–1960). Over the central and eastern study area, precipitation totals increased by approximately 5–15%, while they decreased by 5–10% in the western regions (Panhandle climate division) of the study area (Vose et al., 2014). Given the significant trends in precipitation observed over time, relying on R -factor values derived from outdated rainfall data would lead to inaccuracies.

Another contributing factor is the variation in equations used to calculate rainfall kinetic energy. The equation utilized in the AH703 isoerodent map, developed by Wischmeier and Smith (1958), yields lower rainfall erosivity values for intensities between 12 and 90 mm h^{-1} , while producing higher values of rainfall erosivity for intensities outside this range (McGehee et al., 2022). Additionally, differences in storm identification contribute to the discrepancies. For the AH703 map, rainfall events below 12.5 mm and separated from other events by more than six hours were excluded unless the maximum 15-min intensity exceeded 12.5 mm h^{-1} . This approach significantly reduced the amount of rainfall data considered, resulting in lower erosivity values. In contrast, this study adhered to the USDA-ARS (2013), which included a broader range of rainfall events, yielding higher erosivity values.

The observed discrepancies can also be attributed to differences in mapping methods. The AH703 isoerodent map connects points of equal rainfall erosivity, with values between the lines derived through linear interpolation (Hutchinson, 1988; Renard, 1997). This approach results in a map that exhibits a smooth and gradual spatial trend in rainfall

erosivity (see Fig. 8a). In contrast, the updated map, which interpolates point data directly into a raster format, displays more irregular spatial variations (Fig. 8b).

3.4. Implications and limitations

The primary output of our study is a shapefile (points representing rainfall gauge sites) dataset containing annual and monthly rainfall erosivity factors calculated from over 100 rain gauge sites in Oklahoma containing at least 10 years of recorded data. The annual and monthly rainfall erosivity at rainfall gauge sites can be used as: (1) a validation dataset for new rainfall erosivity models developed for Oklahoma; (2) a training dataset for predicting rainfall erosivity using machine learning techniques; and (3) a reference dataset to project rainfall erosivity from climatic models, such as the General Circulation Models (GCMs).

One of limitations in this study is using different recording periods of rainfall data to compute rainfall erosivity, causing a bias since the rainfall erosivity is not temporally stationary. Considering that generation of rainfall erosivity pool to cover a boarder geographical range, the Mesonet sites with at least 10 years records were selected to estimate rainfall erosivity. Another limitation is the raster maps produced in this study also contain interpolation issues. Unlike the published map compiled in RUSLE which has smooth and continuous surface, some areas on the updated maps represent irregular spatial trends (Fig. 8). Future research should address this issue and further assess the accuracy of the interpolated rainfall erosivity values.

4. Conclusions

This study presented findings on the spatiotemporal variability in rainfall erosivity across the state of Oklahoma. Average annual and monthly rainfall erosivity factors (R -factor and R_m -factor, respectively) were computed using rainfall kinetic energy equation using 5-min interval rainfall data collected between 1994 and Esri, 2024 at 111 Mesonet sites distributed statewide. The rainfall erosivity values for the state were observed to increase from northwest to southeast, and the highest monthly rainfall erosivity (exceeding 500 $\text{MJ mm ha}^{-1} \text{ h}^{-1} \text{ yr}^{-1}$) occurs

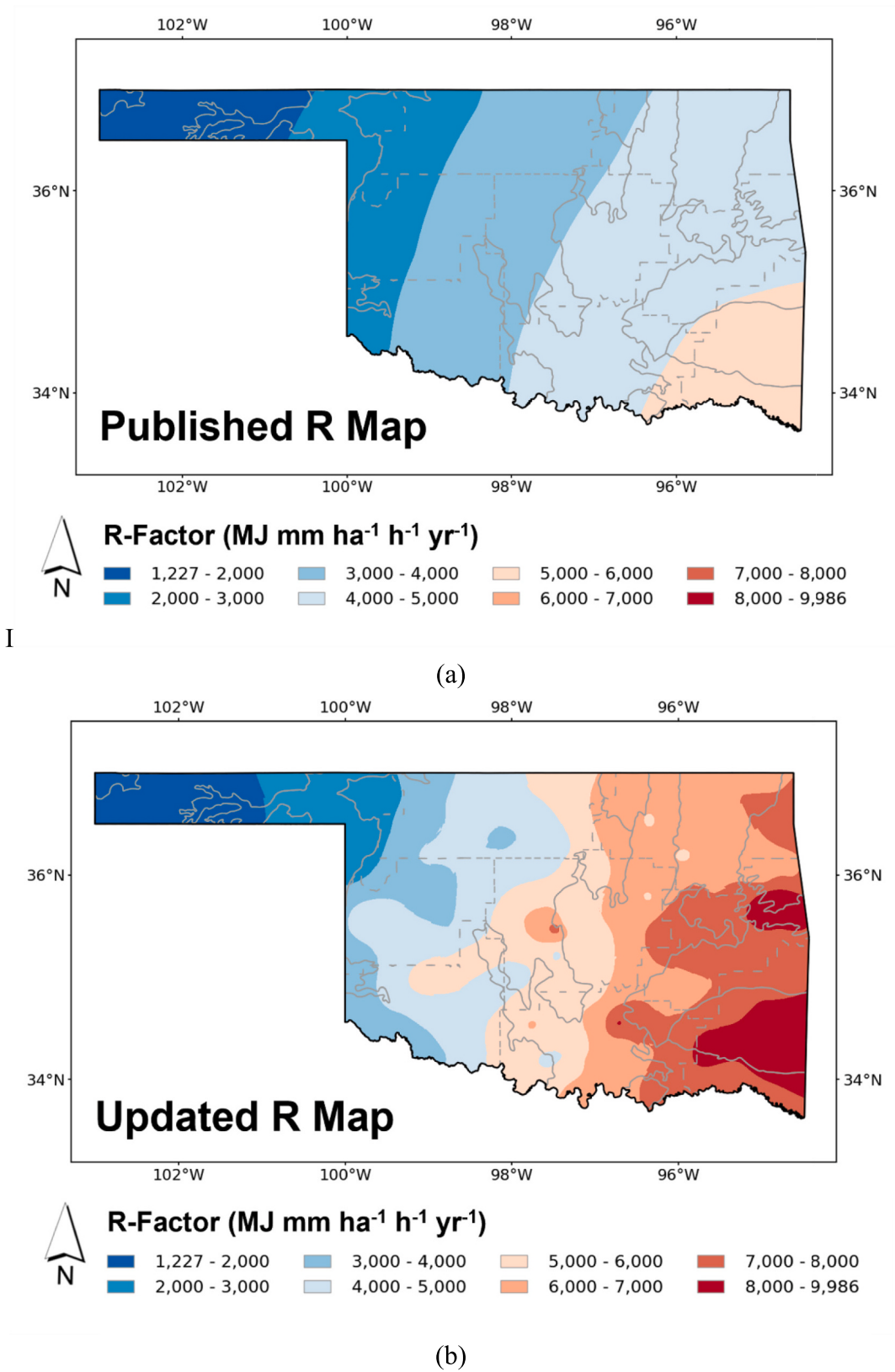


Fig. 8. Raster Maps for Average Annual Erosivity (R-factor; $\text{MJ mm ha}^{-1} \text{ h}^{-1} \text{ yr}^{-1}$): (a) Version Based on Contours as Published in AH703; and (b) Updated Map Developed during the Current Study using Mesonet Data and the Kinetic Energy Equation (Renard, 1997).

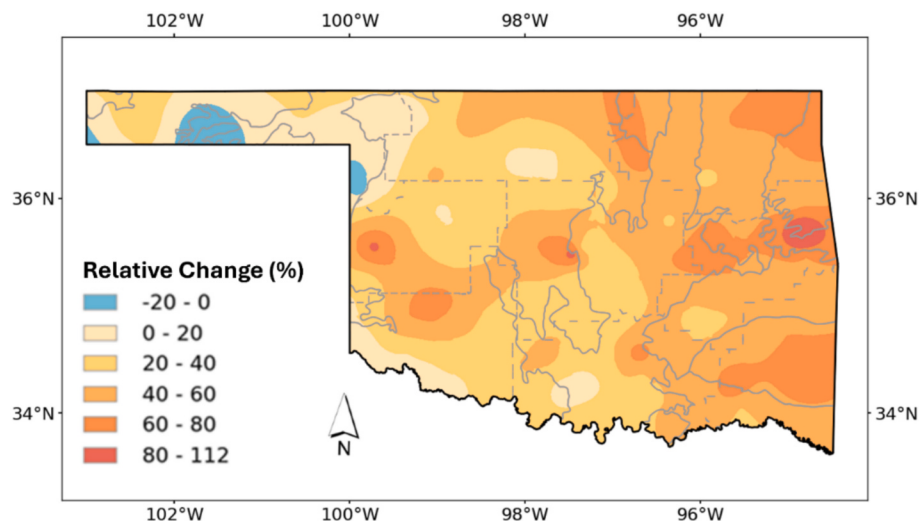


Fig. 9. Distribution of relative difference between updated map and AH703 isoelement map.

in the wet season (from April to October). Monthly variations and spatial patterns in rainfall erosivity factors were examined across climate divisions and Level III ecoregions, which were treated as area divisions within Oklahoma. These analyses aim to facilitate identifying priority areas and months for adaptive strategies for implementing soil erosion. Annual and monthly rainfall erosivity factor maps were generated with 30 m spatial resolution. The value of *R-factor* in the newly developed map ranged up to 9986 MJ mm ha⁻¹ h⁻¹ yr⁻¹, which is greater than the maximum value reported by the original AH703 isoelement map.

CRedit authorship contribution statement

Mengting Chen: Writing – original draft, Formal analysis, Data curation. **Jaime Catherine Schussler:** Writing – review & editing, Supervision, Project administration, Investigation, Conceptualization. **Deb Mishra:** Writing – review & editing, Supervision, Project administration, Investigation, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at <https://doi.org/10.1016/j.catena.2026.109853>.

References

- Alemu, B., 2014. The role of forest and soil carbon sequestrations on climate change mitigation. *Res J Agr Environ Manage* 3 (10), 492–505.
- Boardman, J., Poesen, J., Evans, R., 2003. Socio-economic factors in soil erosion and conservation. *Environ. Sci. Pol.* 6 (1), 1–6. [https://doi.org/10.1016/S1462-9011\(02\)00120-X](https://doi.org/10.1016/S1462-9011(02)00120-X).
- Brock, F.V., Crawford, K.C., Elliott, R.L., Cuperus, G.W., Stadler, S.J., Johnson, H.L., Eilts, M.D., 1995. The Oklahoma Mesonet: a technical overview. *J. Atmos. Ocean. Technol.* 12 (1), 5–19.
- Dabney, S.M., Yoder, D.C., Vieira, D.A.N., 2012. The application of the revised universal soil loss equation, version 2, to evaluate the impacts of alternative climate change

- scenarios on runoff and sediment yield. *J. Soil Water Conserv.* 67 (5), 343–353. <https://doi.org/10.2489/jswc.67.5.343>.
- Dingman, S.L., 2015. *Physical Hydrology*. Waveland press.
- Earls, J., Dixon, B., 2007. Spatial interpolation of rainfall data using ArcGIS: A comparative study. In: *Proceedings of the 27th Annual ESRI International User Conference*, 31, pp. 1–9.
- Edwards, W.M., Owens, L.B., 1991. Large storm effects on total soil erosion. *J. Soil Water Conserv.* 46 (1), 75–78.
- Ellison, W.D., 1950. Soil erosion by rainstorms. *Science* 111 (2880), 245–249. <https://doi.org/10.1126/science.111.2880.245>.
- Esri, 2024. *ArcGIS Pro (Version 3.3.1)*. In: Redlands, C.A. (Ed.), *Environmental Systems Research Institute*. Environmental Systems Research Institute.
- Flanagan, D.C., McGehee, R.P., Srivastava, A., 2020. Evaluation of different precipitation inputs to WEPP. In: *2020 ASABE Annual International Virtual Meeting*. American Society of Agricultural and Biological Engineers, p. 1. <https://doi.org/10.13031/aim.202000740>.
- Garbrecht, J.D., Zhang, X.C., 2015. Soil erosion from winter wheat cropland under climate change in Central Oklahoma. *Appl. Eng. Agric.* 31 (3), 439–454. <https://doi.org/10.13031/aea.31.10998>.
- Gilley, J.E., Doran, J.W., Dao, T.H., 1997. Runoff, erosion, and soil quality characteristics of a former conservation reserve program site in southwestern Oklahoma. *Appl. Eng. Agric.* 13 (5), 617–622. <https://doi.org/10.13031/2013.21650>.
- Gourley, B., Park, C.N., 2012. Mesas to marshes: a look at the unexpectedly diverse ecoregions of Oklahoma. *Rangelands* 34 (6), 64–65.
- Guttman, N.B., Quayle, R.G., 1996. A historical perspective of US climate divisions. *Bull. Am. Meteorol. Soc.* 77 (2), 293–304. <https://doi.org/10.1175/1520-0477>.
- Harmel, R.D., Haan, C.T., Dutnell, R.C., 1999. Evaluation of Rosgen's streambank erosion potential assessment in northeast Oklahoma¹. *JAWRA Journal of the American Water Resources Association* 35 (1), 113–121.
- He, X., Miao, Z., Wang, Y., Yang, L., Zhang, Z., 2024. Response of soil erosion to climate change and vegetation restoration in the Ganjiang River basin. *China. Ecological Indicators* 158, 111429. <https://doi.org/10.1016/j.ecolind.2023.111429>.
- Hollinger, S.E., Angel, J.R., Palecki, M.A., 2002. Spatial distribution, variation, and trends in storm precipitation characteristics associated with soil erosion in the United States. *ISWS Contract Report CR-2002-08*.
- Huff, F.A., Angel, J.R., 1992. *Rainfall frequency atlas of the Midwest*. Bulletin (Illinois State Water Survey) no. 71.
- Hutchinson, M.F., 1988. Calculation of hydrologically sound digital elevation models. In: *Proceedings of the Third International Symposium on Spatial Data Handling* (vol. 133, pp. 117–133).
- Issaka, S., Ashraf, M.A., 2017. Impact of soil erosion and degradation on water quality: a review. *Geology, Ecology, and Landscapes* 1 (1), 1–11. <https://doi.org/10.1080/24749508.2017.1301053>.
- Jordahl, K., 2014. *GeoPandas: Python Tools for Geographic Data*. URL: <https://Github>.
- Karl, T., Koss, W.J., 1984. *Regional and National Monthly, Seasonal, and Annual Temperature Weighted by Area*, pp. 1895–1983.
- Kloesel, K., Bartush, B., Banner, J., Brown, D.P., Lemery, J., Lin, L., Loeffler, C., McManus, G., Mullens, E., Nielsen-Gammon, J., Shafer, M., 2018. *Southern great plains. USDA miscellaneous Publication* 1343 (2), 978–1026.
- Larson, W.E., Lindstrom, M.J., Schumacher, T.E., 1997. The role of severe storms in soil erosion: a problem needing consideration. *J. Soil Water Conserv.* 52 (2), 90–95.
- McGehee, R., Srivastava, P., 2018. Benchmarking reliable erosion indices from quarter-hour station data for climate studies in the southeastern United States. *J. Soil Water Conserv.* 73 (4), 363–376. <https://doi.org/10.2489/jswc.73.4.363>.
- McGehee, R.P., Flanagan, D.C., Srivastava, P., Nearing, M.A., 2022. Rainfall erosivity: Essential historical, conceptual, and practical perspectives for continued application. In: *Precipitation*. Elsevier, pp. 373–394. <https://doi.org/10.1016/B978-0-12-822699-5.00014-8>.

- McKinney, W., 2010. Data structures for statistical computing in Python. In *SciPy* (vol. 445, no. 1, pp. 51–56).
- Meena, N.K., Gautam, R., Tiwari, P., Sharma, P., 2017. Nutrient losses in soil due to erosion. *Journal of Pharmacognosy and Phytochemistry* 6 (6S), 1009–1011.
- Moriasi, D.N., Starks, P.J., Steiner, J.L., Zhang, X.C., Garbrecht, J.D., Glasgow, S., 2020. An overview of research into conservation practice effects on soil and water resources in the upper Washita Basin, Oklahoma, United States. *J. Soil Water Conserv.* 75 (3), 330–339. <https://doi.org/10.2489/jswc.75.3.330> b.
- Nugues, M.M., Roberts, C.M., 2003. Coral mortality and interaction with algae in relation to sedimentation. *Coral Reefs* 22, 507–516. <https://doi.org/10.1007/s00338-003-0338-x>.
- Oklahoma Climatological Survey, 2024. Climate of Oklahoma. Retrieved from. <https://www.ou.edu/ocs/oklahoma-climate>.
- Oliveira, P.T.S., Wendland, E., Nearing, M.A., 2013. Rainfall erosivity in Brazil: A review. *Catena* 100, 139–147. <https://doi.org/10.1016/j.catena.2012.08.006>.
- Oliver, M.A., Webster, R., 1990. Kriging: a method of interpolation for geographical information systems. *Int. J. Geogr. Inf. Syst.* 4 (3), 313–332. <https://doi.org/10.1080/02693799008941549>.
- Omernik, J.M., 1987. Ecoregions of the conterminous United States. *Ann. Assoc. Am. Geogr.* 77 (1), 118–125. <https://doi.org/10.1111/j.1467-8306.1987.tb00149.x>.
- Omernik, J.M., Griffith, G.E., 2014. Ecoregions of the conterminous United States: evolution of a hierarchical spatial framework. *Environ. Manag.* 54, 1249–1266. <https://doi.org/10.1007/s00267-014-0364-1>.
- Panagos, P., Hengl, T., Wheeler, I., Marcinkowski, P., Rukeza, M.B., Yu, B., Yang, J.E., Miao, C., Chattopadhyay, N., Sadeghi, S.H., Levi, Y., 2023. Global rainfall erosivity database (GloREda) and monthly R-factor data at 1 km spatial resolution. *Data Brief* 50, 109482. <https://doi.org/10.1016/j.dib.2023.109482>.
- Rahmani, V., Hutchinson, S.L., Harrington, J.A., Hutchinson, J.M., 2016. Analysis of frequency and magnitude of extreme rainfall events with potential impacts on flooding: a case study from the Central United States. *Int. J. Climatol.* 36 (10). <https://doi.org/10.1002/joc.4577>.
- Renard, K.G., 1997. Predicting Soil erosion by Water: A Guide to Conservation Planning with the Revised Universal Soil Loss Equation (RUSLE). US Department of Agriculture, Agricultural Research Service.
- Rice, C.W., Reed, D., 2007. Soil Carbon Sequestration and Greenhouse Gas Mitigation: A Role for American Agriculture. Kansas State University, Manhattan.
- Sartori, M., Philippidis, G., Ferrari, E., Borrelli, P., Lugato, E., Montanarella, L., Panagos, P., 2019. A linkage between the biophysical and the economic: assessing the global market impacts of soil erosion. *Land Use Policy* 86, 299–312. <https://doi.org/10.1016/j.landusepol.2019.05.014>.
- Smith, D.D., Wischmeier, W.H., 1962. Rainfall erosion. In: *Advances in Agronomy*, 14, pp. 109–148. [https://doi.org/10.1016/S0065-2113\(08\)60437-X](https://doi.org/10.1016/S0065-2113(08)60437-X).
- Thaler, E.A., Larsen, I.J., Yu, Q., 2021. The extent of soil loss across the US Corn Belt. *Proc. Natl. Acad. Sci.* 118 (8), e1922375118. <https://doi.org/10.1073/pnas.1922375118>.
- USDA-ARS, 2013. Science Documentation: Revised Universal Soil Loss Equation, Version 2 (RUSLE 2). USDA-Agricultural Research Service Washington, DC, USA.
- Vose, R.S., Applequist, S., Squires, M., Durre, I., Menne, M.J., Williams Jr., C.N., Fenimore, C., Gleason, K., Arndt, D., 2014. Improved historical temperature and precipitation time series for US climate divisions. *J. Appl. Meteorol. Climatol.* 53 (5), 1232–1251. <https://doi.org/10.1175/JAMC-D-13-0248.1>.
- Wang, W., Yin, S., Xie, Y., Liu, B., Liu, Y., 2016. Effects of four storm patterns on soil loss from five soils under natural rainfall. *Catena* 141, 56–65. <https://doi.org/10.1016/j.catena.2016.02.019>.
- Warren, J., 2010. Raindrops and Bombs: The erosion Process. Oklahoma Cooperative Extension Service.
- Wischmeier, W.H., 1959. A rainfall erosion index for a universal soil-loss equation. *Soil Sci. Soc. Am. J.* 23 (3), 246–249. <https://doi.org/10.2136/sssaj1959.03615995002300030027x>.
- Wischmeier, W.H., Smith, D.D., 1958. Rainfall energy and its relationship to soil loss. *EOS Trans. Am. Geophys. Union* 39 (2), 285–291.
- Wischmeier, Walter H., Smith, Dwight David, 1978. Predicting Rainfall Erosion Losses: A Guide to Conservation Planning. 537. Department of Agriculture, Science and Education Administration.